

Assimilation of AMSR-E data and application to the initialization of soil moisture reservoirs in a seasonal forecasting system

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Motivation	Seasonal climate prediction & land initialization
Results	Global assimilation of SMMR retrievals
In Progress	Assimilation of AMSR-E retrievals

1 – GEST, University of Maryland, Baltimore County

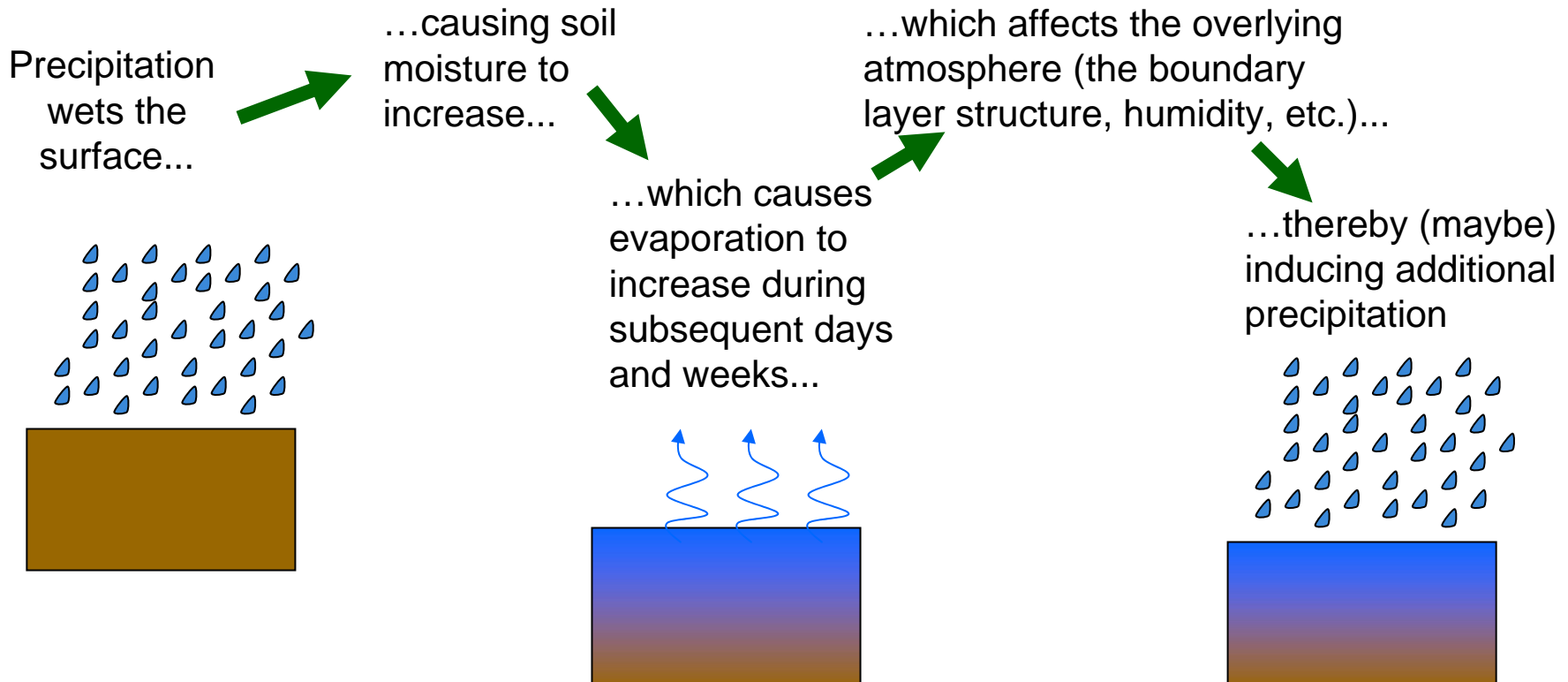
2 – Global Modeling and Assimilation Office, NASA

3 – Hydrological Sciences Branch, NASA-GSFC

4 – USDA

5 – George Mason University

A simple view of land-atmosphere feedback



Perhaps such feedback contributes to predictability?

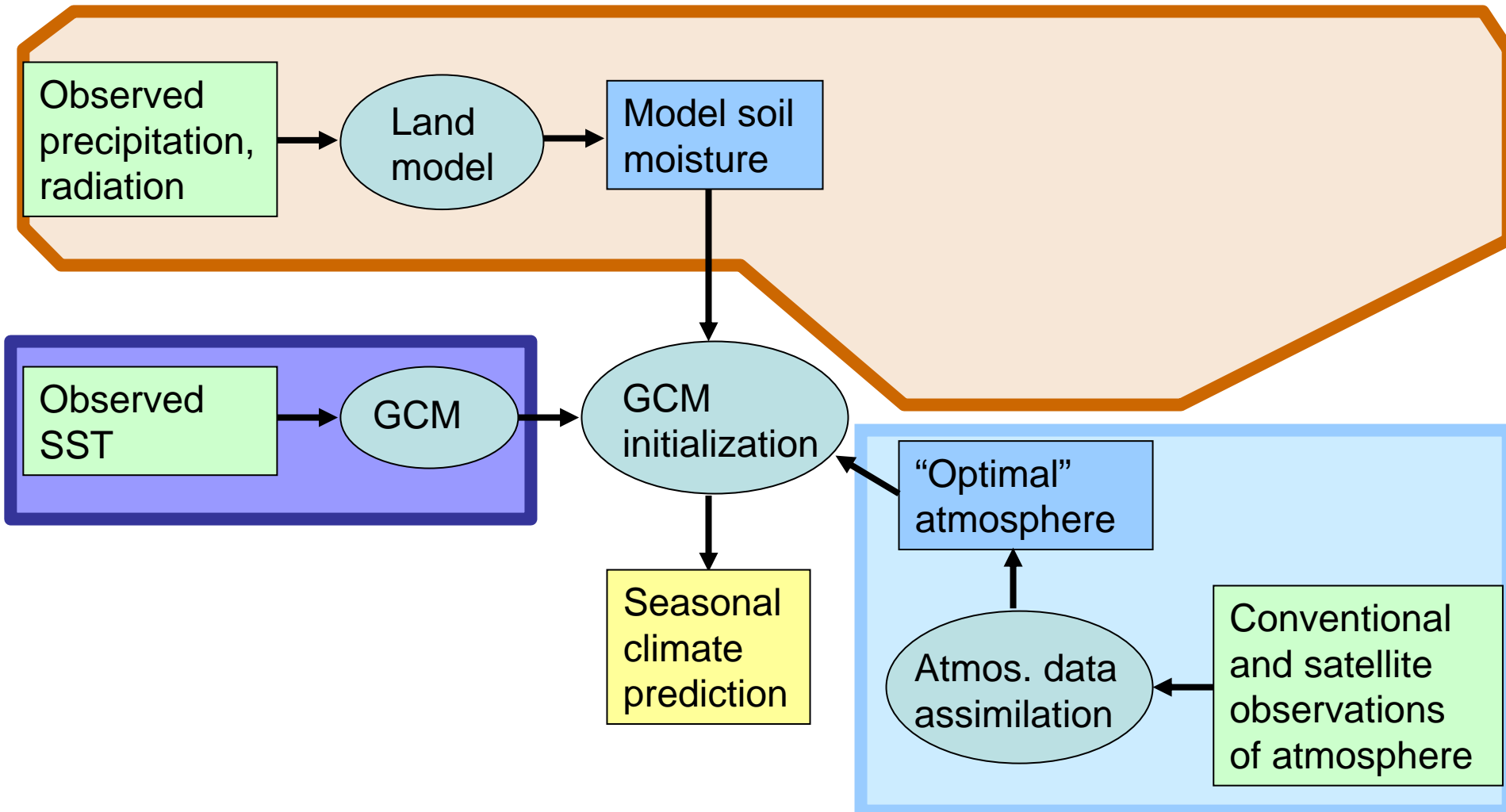
Two things must happen:

1. A soil moisture anomaly must be “remembered” into the forecast period.
2. The atmosphere must respond predictably to soil moisture anomalies.

e.g. Koster et al., *J. Hydromet.*, 2004; Koster et al., *Science*, 2004

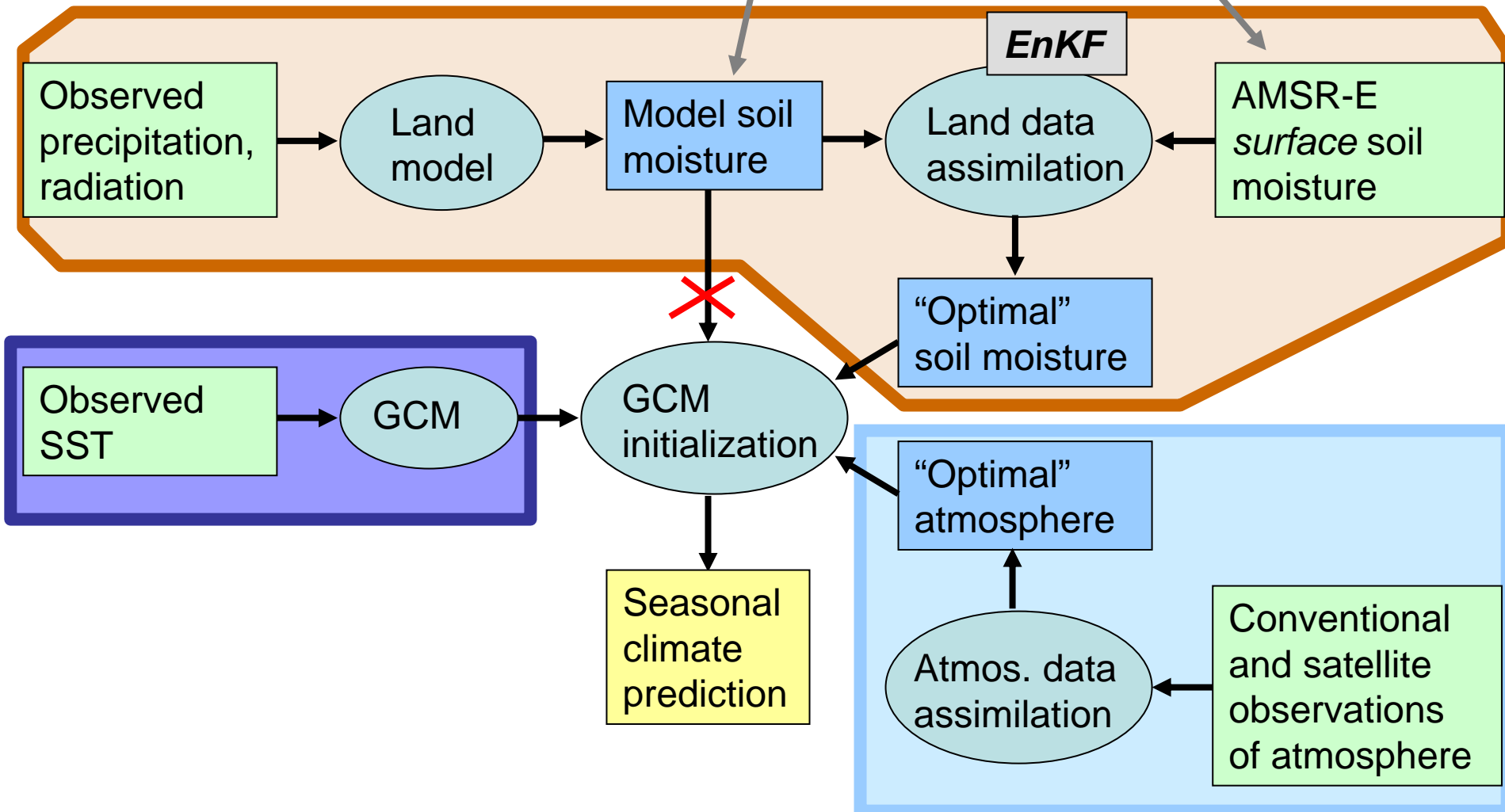
NASA seasonal forecast initialization

Operational system (since April 2004)

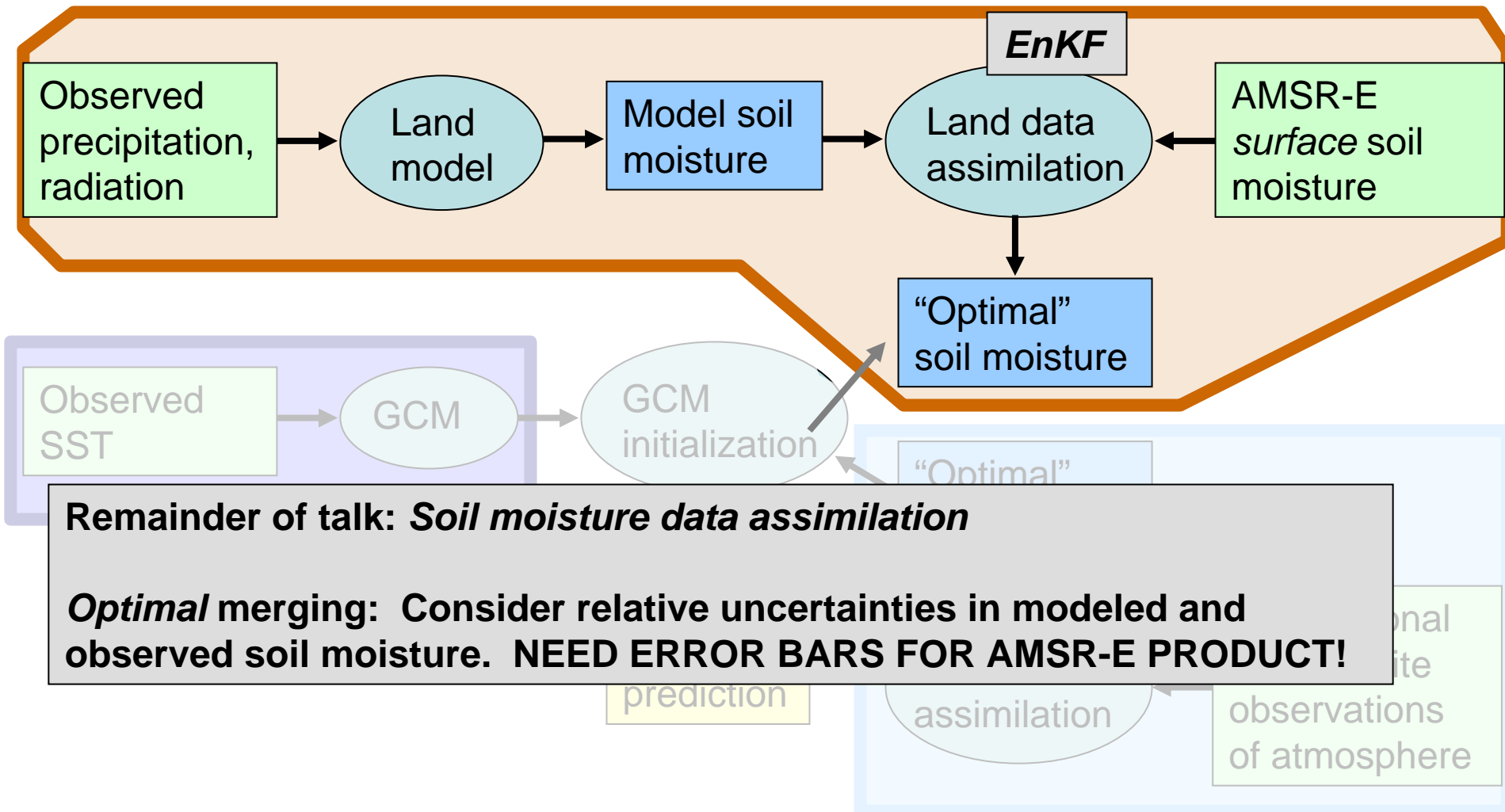


NASA seasonal forecast initialization

Future system: AMSR-E assimilation merges information from **model and **observations**.**



Soil moisture assimilation



Motivation

Seasonal climate prediction & land initialization

Results

Global assimilation of **SMMR** retrievals

In Progress

Assimilation of **AMSR-E** retrievals

Results from SMMR

ASSIMILATE

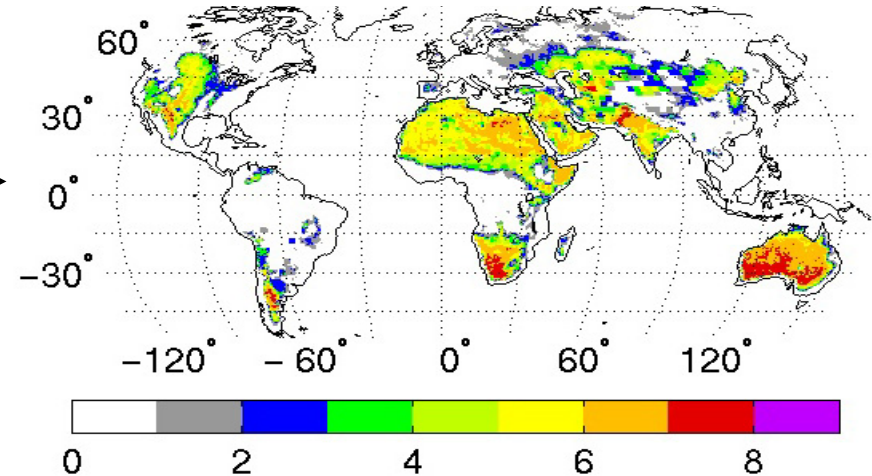
1. SMMR (1978-87)

Satellite retrievals (Owe et al.)

(upper 1.25cm, ~140km, ~3 days)



Avg. # of SMMR data per month (79-87)



Not available under dense vegetation,
close to water surfaces, in frozen soil.

2. Catchment Model (CLSM) (1979-93)

Model results with **observation-corrected**
meteorological forcing (Berg, Famiglietti,
et al.)

(upper 2cm, ~40...150km, 6h)

3. Ground data

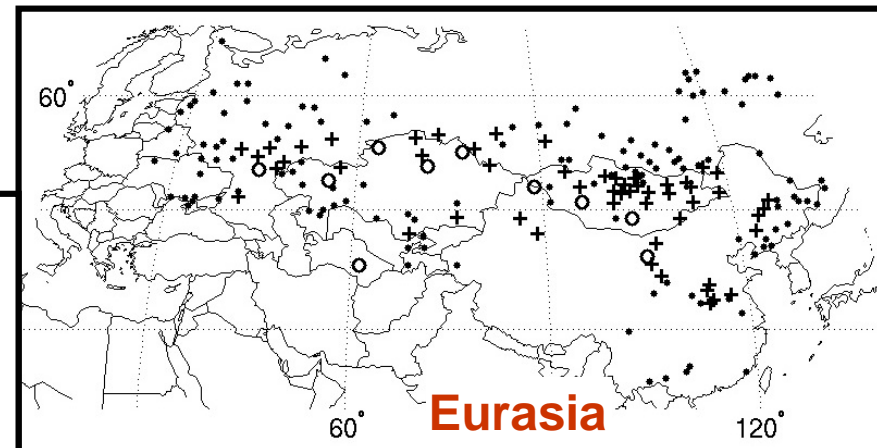
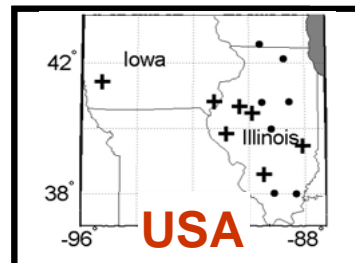
Global Soil Moisture Data Bank (GSMDDB;
Robock et al)

(upper 5...10cm, point scale, ~10 days)

~200 stations total

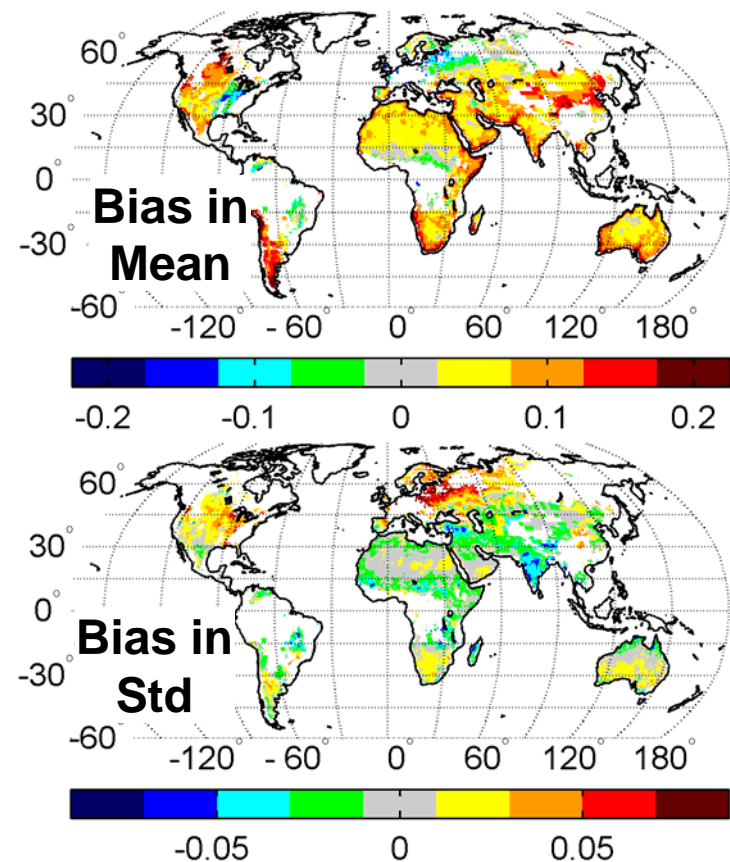
~70 included in analysis

VALIDATE



Global soil moisture climatology?

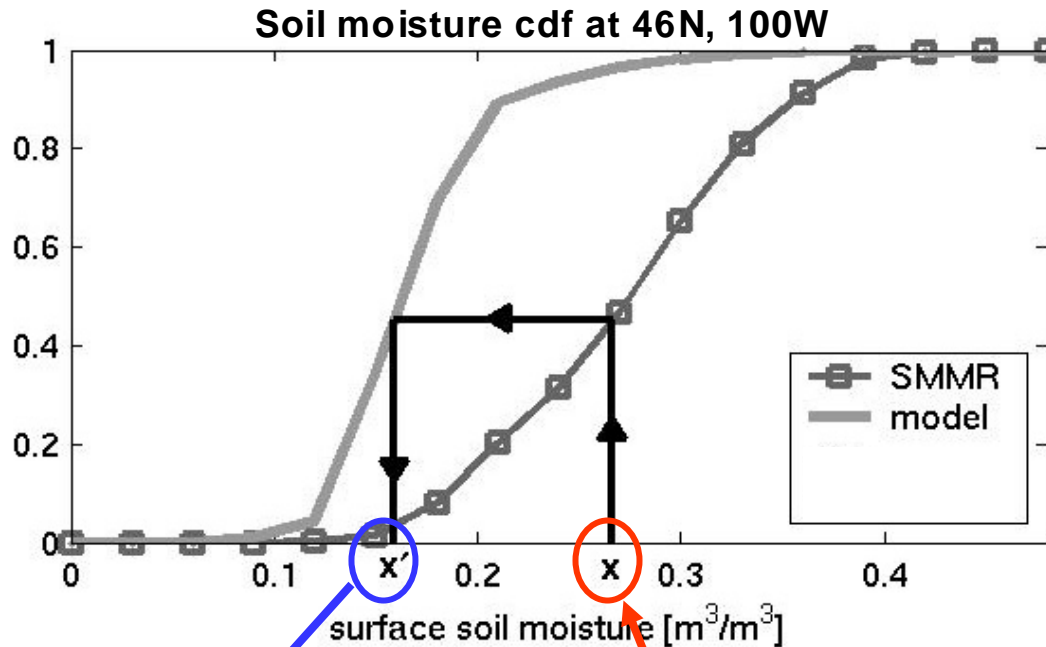
Bias between model and SMMR soil moisture



1. Strong global and regional **biases** in all moments.
 2. Satellite and model agree **equally well** (or poorly...) with ground observations \Rightarrow no agreed climatology.
 3. For seasonal forecasts, need only **normalized anomalies**.
- \Rightarrow *Scale satellite data before assimilation into a model.*

Reichle et al., *J. Hydromet*, 2004

Soil moisture scaling for data assimilation



2. Find soil moisture that produces the same CDF value on the corresponding model CDF \Rightarrow “scaled” satellite measurement for assimilation.

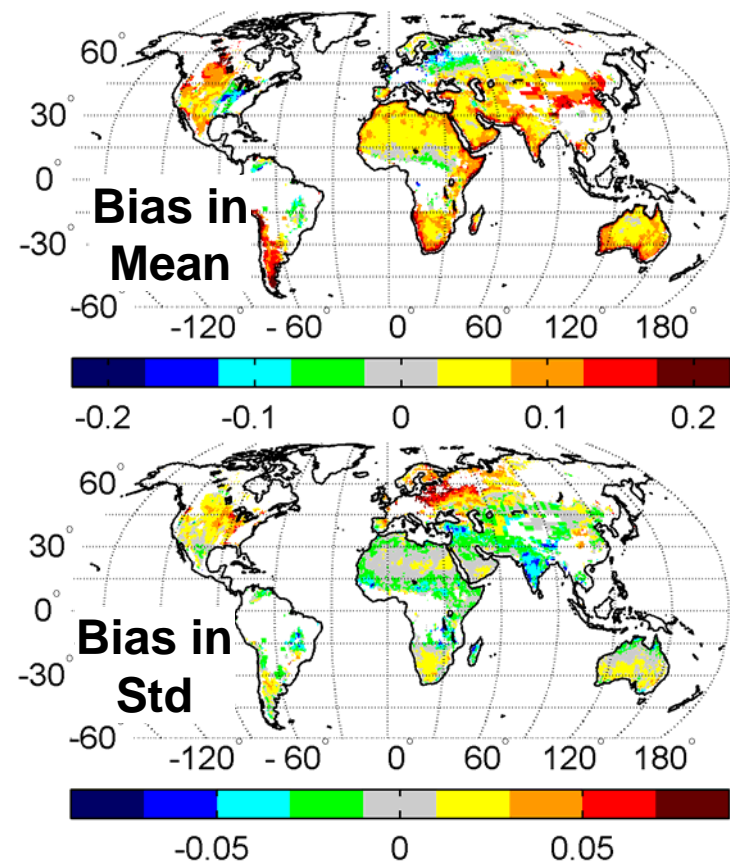
1. At every location, find percentile of a given satellite measurement on the satellite’s climatological cumulative distribution function (CDF).

In short: Assimilate percentiles.

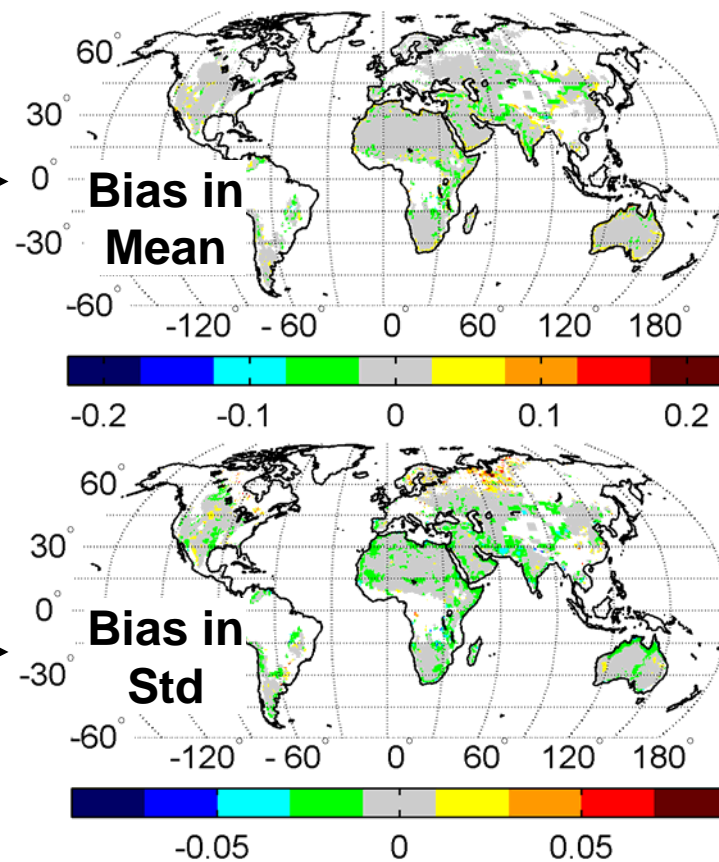
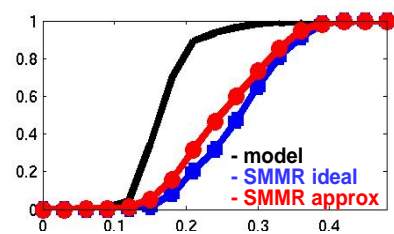
Soil moisture scaling for data assimilation

ORIGINAL 9-year data sets
(model & SMMR soil moisture)

SCALED 9-year data sets
(model & SMMR soil moisture)



CDF scaling based
on 1 year of
satellite data



Reichle et al., *J. Hydromet*, 2004

Reichle & Koster, *GRL* 2004

1 year of satellite data sufficient for considerable reduction in long-term bias.

Results from SMMR

ASSIMILATE

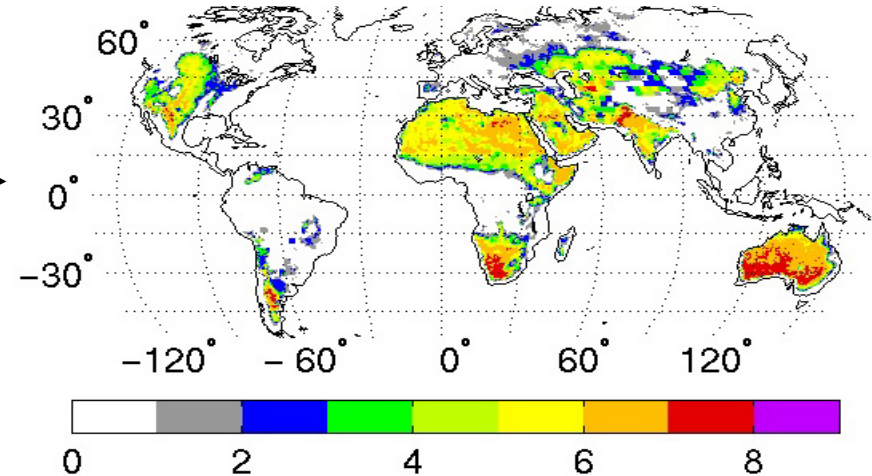
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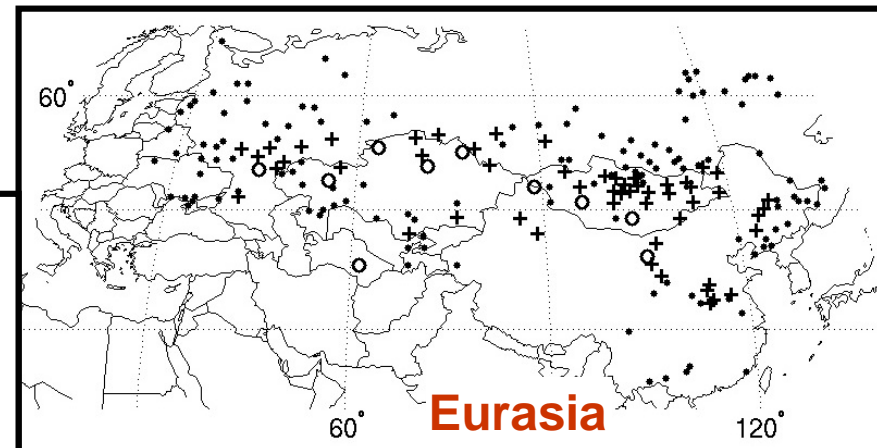
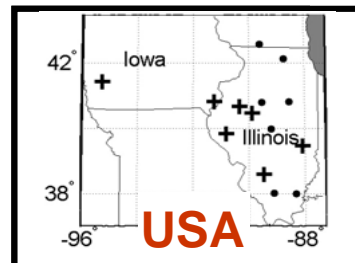
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(upper 5...10cm, point scale, ~10 days)

~200 stations total

~70 included in analysis

VALIDATE



Validation against in situ data

		Time series correlation coeff. with in situ data [-] (with 95% confidence interval)			Confidence levels: Improvement of assimilation over	
	N	SMMR	Model	Assim.	SMMR	Model
Surface soil moisture	77	.44±.03	.43±.03	.50±.03	99.7%	99.9%
Surface anomalies	66	.32±.03	.36±.03	.43±.03	99.9%	99.9%
Root zone soil moisture	59	n/a	.46±.03	.50±.03	n/a	97%
Root zone anomalies	33	n/a	.32±.05	.35±.05	n/a	80%

Assimilation product agrees better with ground data than SMMR or model alone.

Modest increase may be close to maximum possible with *imperfect* in situ data.

Modern satellite (AMSR-E), forcing, and validation data should increase skill.

Motivation

Seasonal climate prediction & land initialization

Results

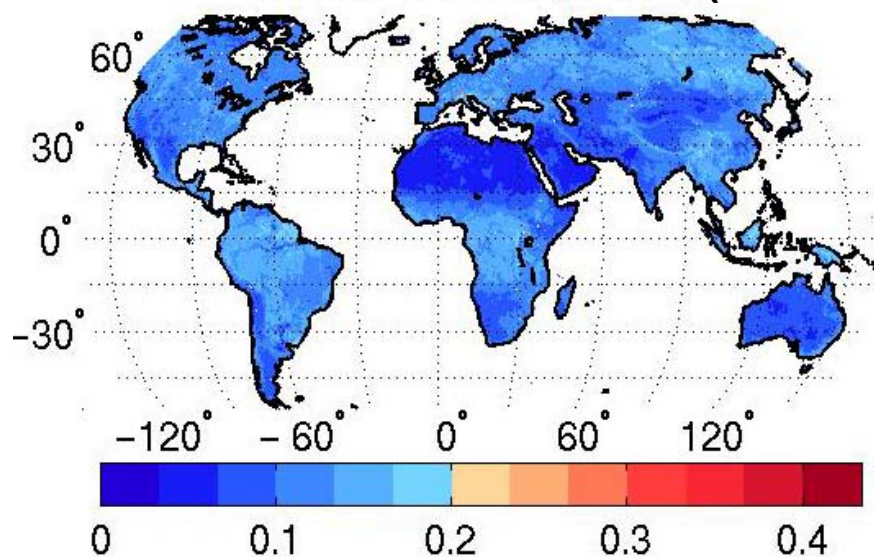
Global assimilation of **SMMR** retrievals

In Progress

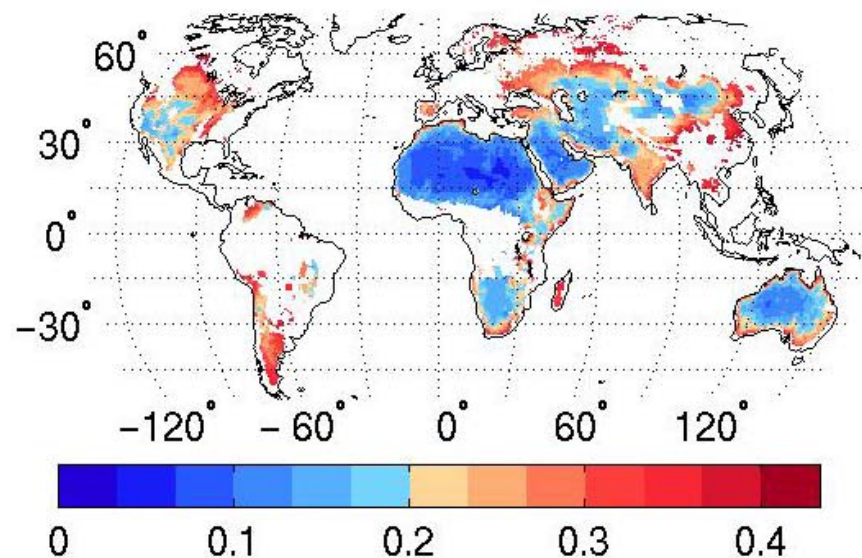
Assimilation of **AMSR-E** retrievals

Time series stats of AMSR-E and SMMR retrievals

AMSR-E mean [m^3m^{-3}] (06/02-05/05)

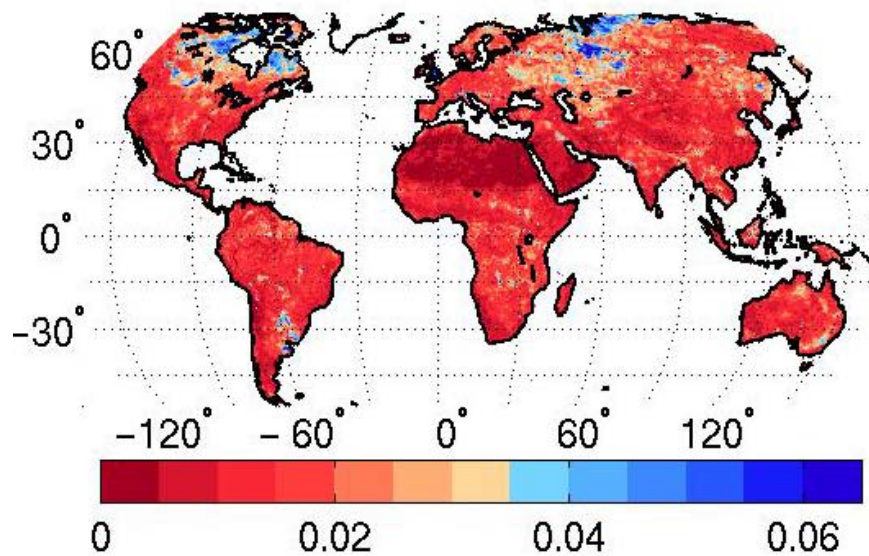


SMMR mean [m^3m^{-3}] (01/79-08/87)

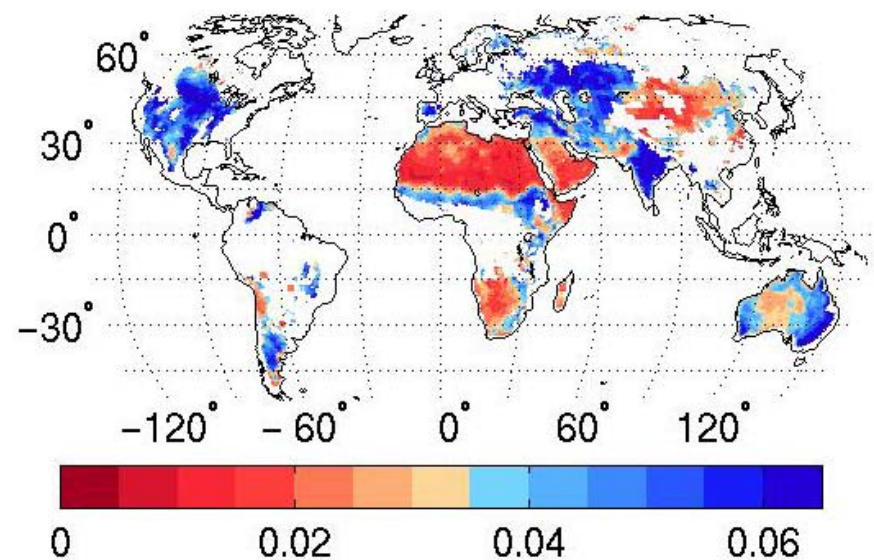


Time series stats of AMSR-E and SMMR retrievals

AMSR-E std [m^3m^{-3}] (06/02-05/05)

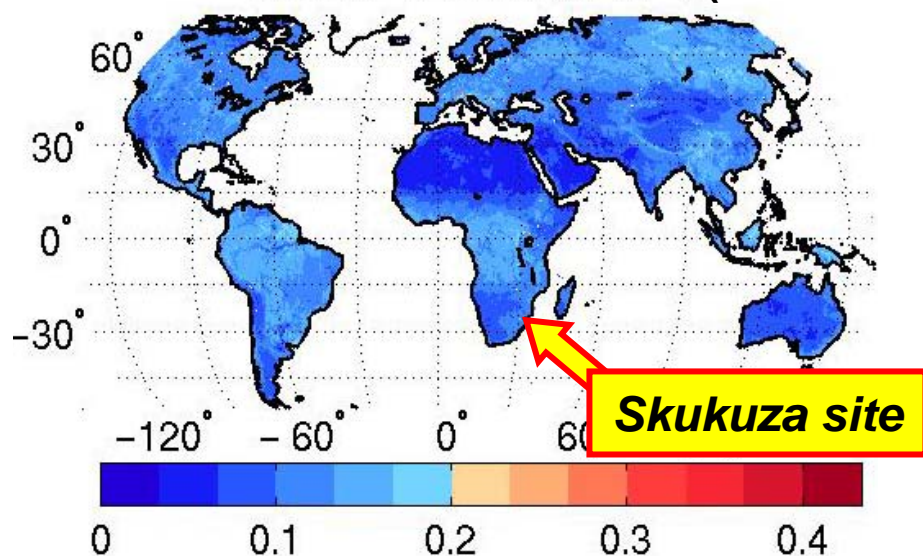


SMMR std [m^3m^{-3}] (01/79-08/87)

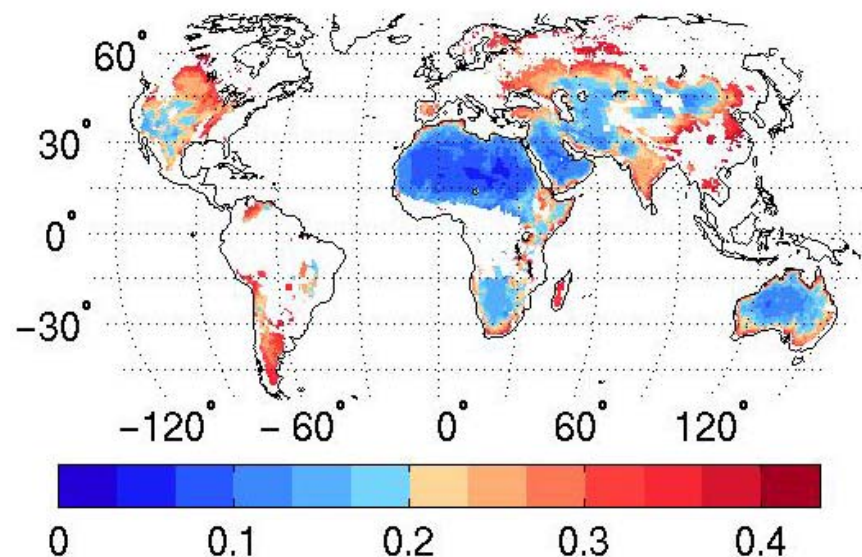


Time series stats of AMSR-E and SMMR retrievals

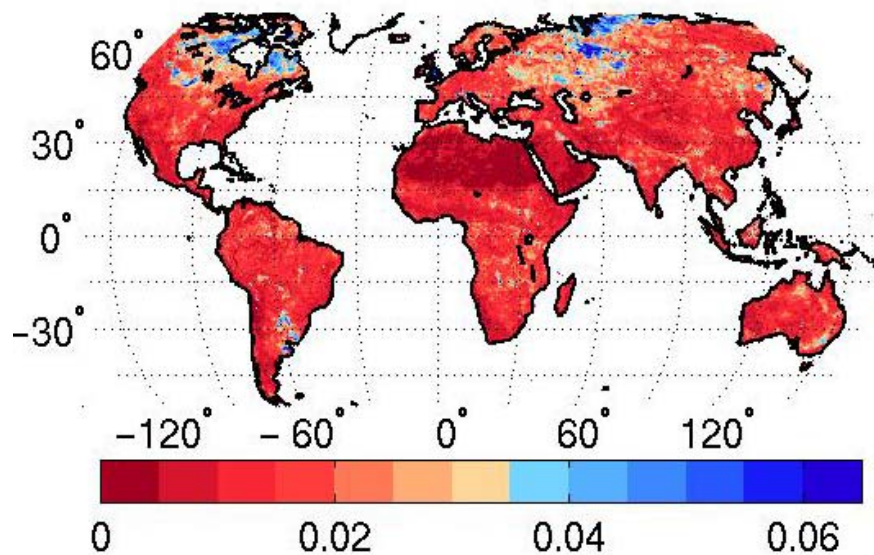
AMSR-E mean [m^3m^{-3}] (06/02-05/05)



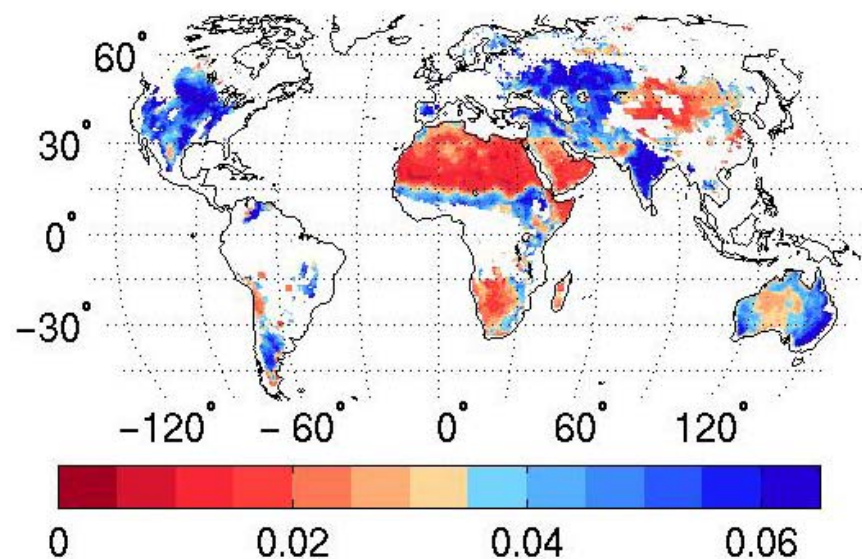
SMMR mean [m^3m^{-3}] (01/79-08/87)



AMSR-E std [m^3m^{-3}] (06/02-05/05)

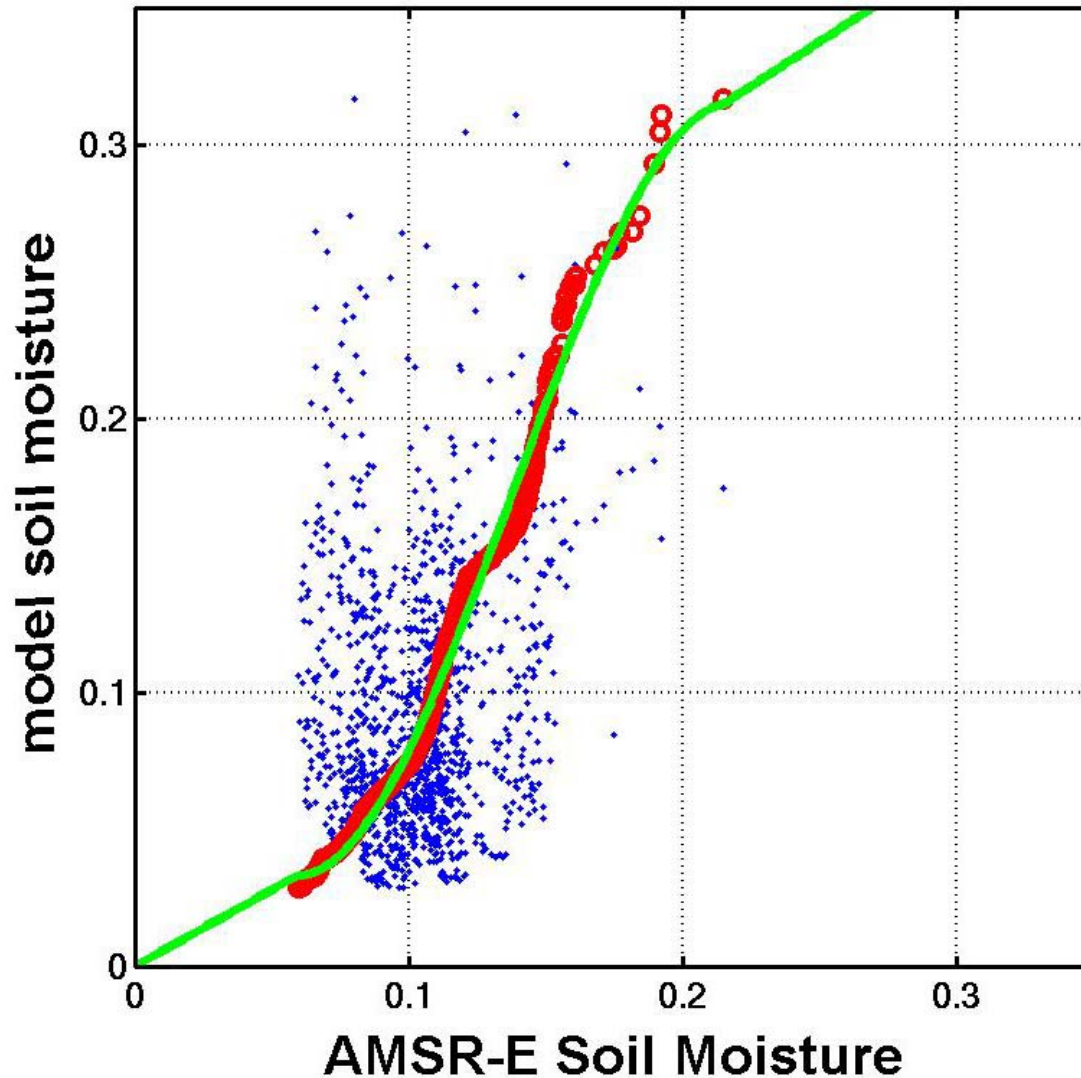


SMMR std [m^3m^{-3}] (01/79-08/87)



Comparison of AMSR-E and model soil moisture

Skukuza (25.0 S, 31.5 E)



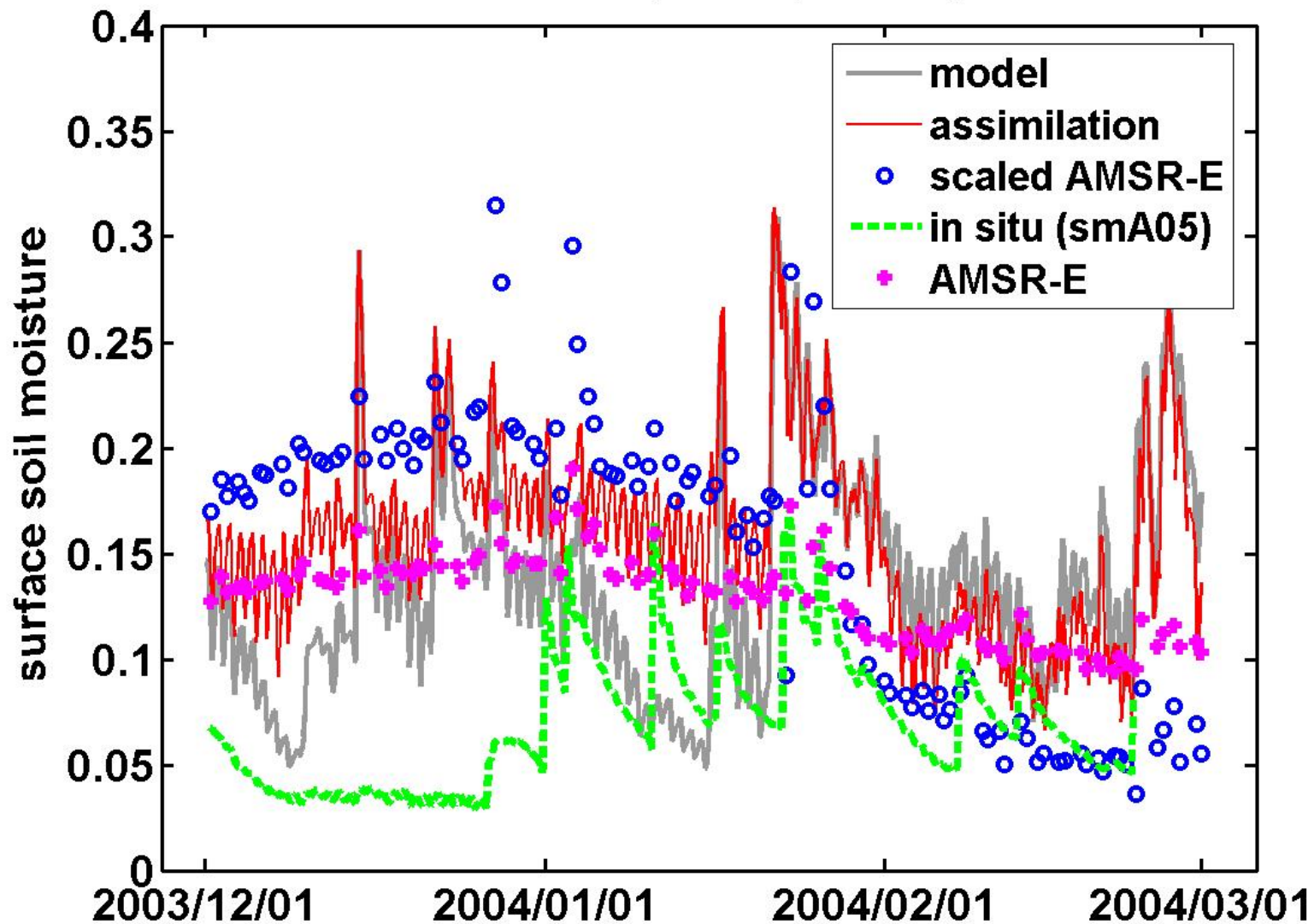
AMSR-E and model soil moisture show large differences in mean, variability, and dynamic range.

Time series are uncorrelated ($R^2=.02$).

• mod v. obs scatter ($R^2=0.02$) ○ cdf match — cdf match (poly/lin fit)

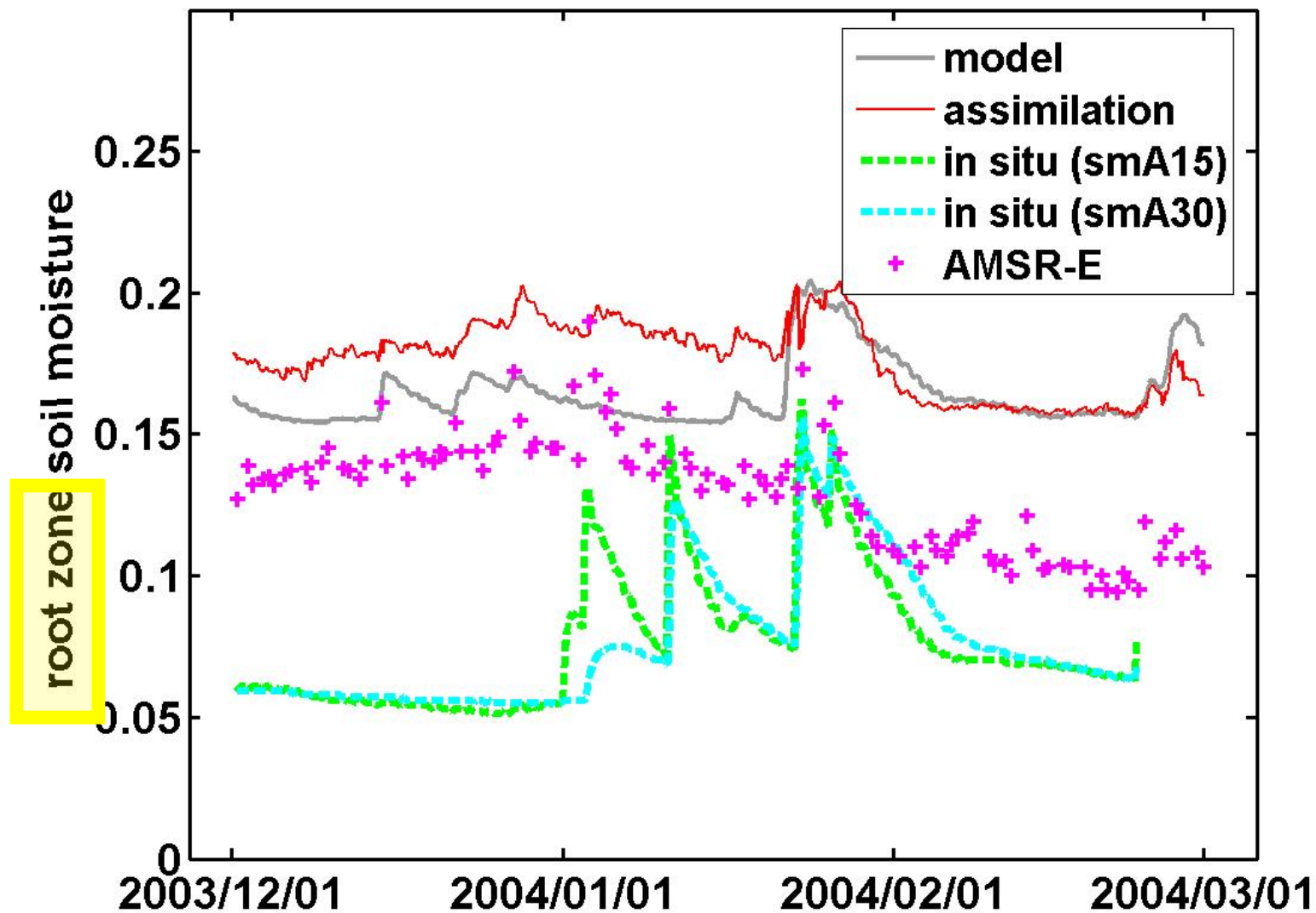
Assimilation of AMSR-E soil moisture

Skukuza (25.0 S, 31.5 E)



Assimilation of AMSR-E soil moisture

Skukuza (25.0 S, 31.5 E)



Validation against in situ data

		Time series correlation coeff. with in situ data [-] <i>(Jun 02 – Apr 05, monthly average)</i>		
	N	AMSR-E	Model	Assim.
Surface soil moisture	1	-.04	.56	.17
Root zone soil moisture	1	n/a	.33	.08

For this site, the assimilation product does NOT agree better with ground data than model alone.

Biggest concern are AMSR-E retrievals.

Conclusions

Results:

Improved land initialization enhances sub-seasonal prediction skill.

SMMR assimilation improves land initialization.

AMSR-E assimilation system implemented.

AMSR-E assimilation results undergoing validation.

Biggest concern at this time are AMSR-E soil moisture retrievals.

Outlook:

Continue assessment of soil moisture estimates.

Impact of SMMR and AMSR-E assimilation on seasonal predictions.

THE END.

Work Plan

TASK I – Preparation of input data sets.

TASK II – Assimilation and analysis of soil moisture data

Prepare four different *soil moisture datasets*: Integrate land model with

1. GCM-produced precip./radiation (GCM forced with observed SST)
2. observed precip./radiation
3. GCM-produced precip./radiation + assimilation of AMSR-E soil moisture
4. observed precip./radiation + assimilation of AMSR-E soil moisture

Assess impact of AMSR-E data on soil moisture estimation.

TASK III – Experimental prediction

Ensemble *seasonal forecast experiments* with initial conditions from TASK II.

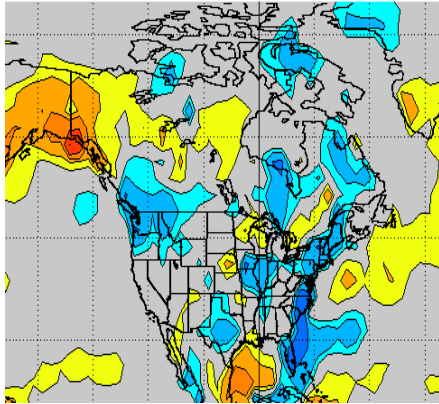
Assess impact of observed precip./radiation and AMSR-E assimilation on seasonal forecasts.

Establish routine AMSR-E land assimilation in operational GMAO seasonal forecasting system.

Sample NASA forecast – August 2004

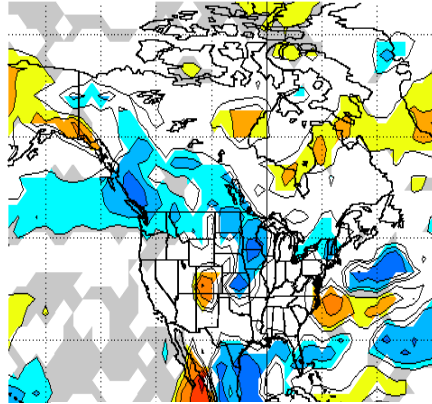
Validation (CAMS)

CAMS Precipitation Aug. 2004



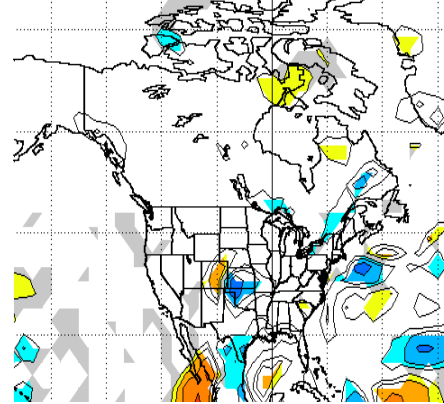
Forecast 1st month

Aug. 2004 Precipitation init:2004/08/01



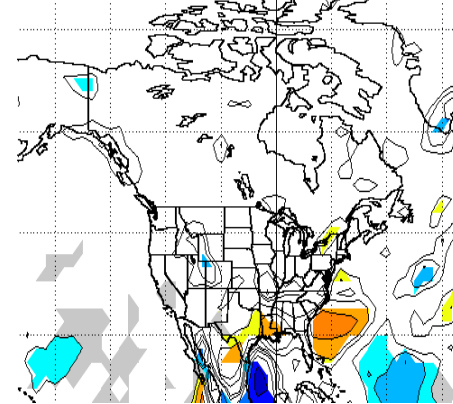
Forecast 2nd month

Aug. 2004 Precipitation init:2004/07/01



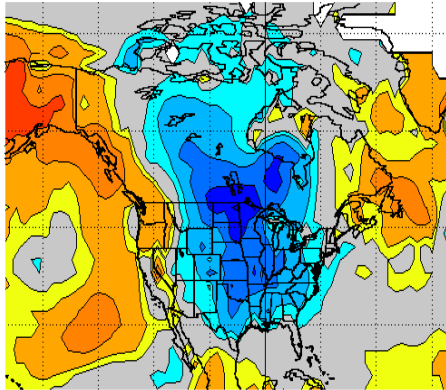
AMIP ensemble (uses only SST information)

AMIP Aug. 2004 Precipitation

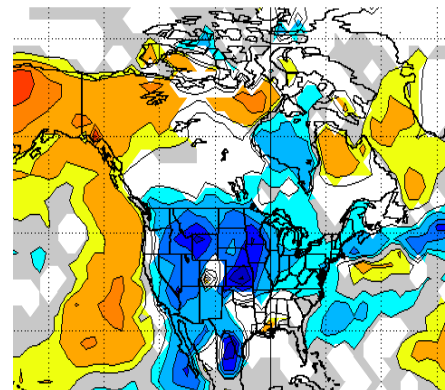


-16 -8 -4 -2 -1 -0.5 0.5 1 2 4 8 16 mm/day

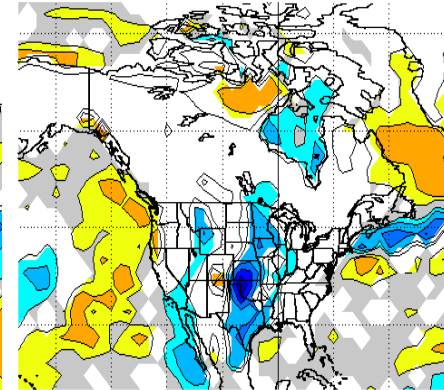
CAMS Surface Temperature Aug. 2004



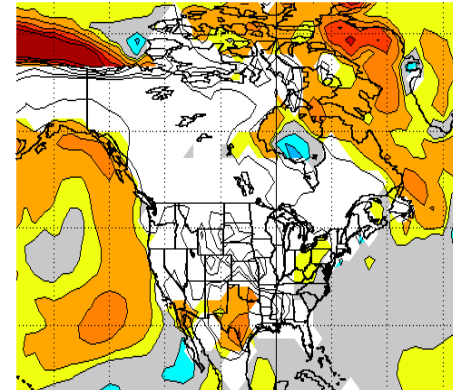
Aug. 2004 Temperature init:2004/08/01



Aug. 2004 Temperature init:2004/07/01



AMIP Aug. 2004 Temperature



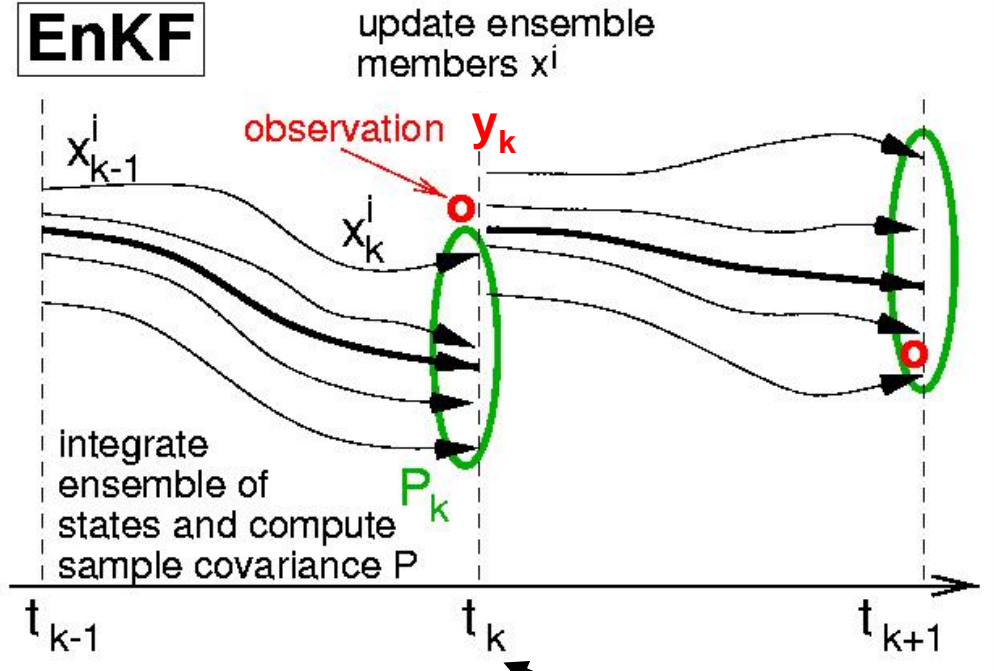
-5 -4 -3 -2 -1 -0.5 0.5 1 2 3 4 5 °C

Precipitation

Temperature

Soil moisture assimilation

EnKF



Nonlinearly propagates ensemble of model trajectories.
Can account for wide range of model errors (incl. non-additive).

Approx.: **Ensemble size.**

Linearized update.

x_k^i state vector (eg soil moisture)

P_k state error covariance

R_k observation error covariance

Propagation t_{k-1} to t_k :

$$x_k^{i+} = f(x_{k-1}^{i-}) + w_k^i$$

w = model error

Update at t_k :

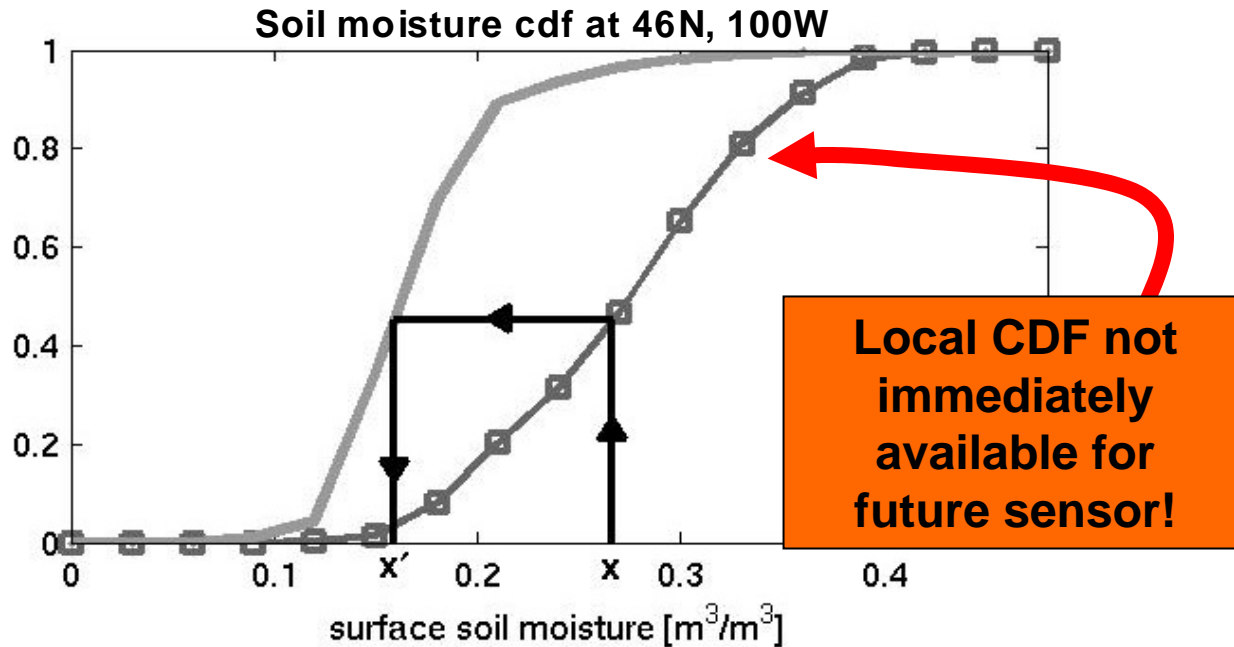
$$x_k^{i+} = x_k^{i-} + K_k(y_k^i - x_k^{i-})$$

for each ensemble member $i=1 \dots N$

$$K_k = P_k (P_k + R_k)^{-1}$$

with P_k computed from ensemble spread

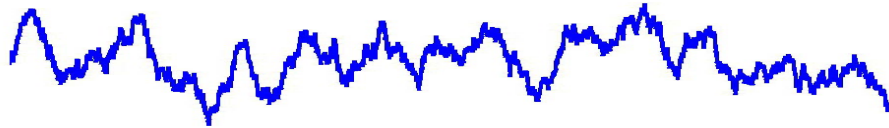
Soil moisture scaling for data assimilation



Solution:

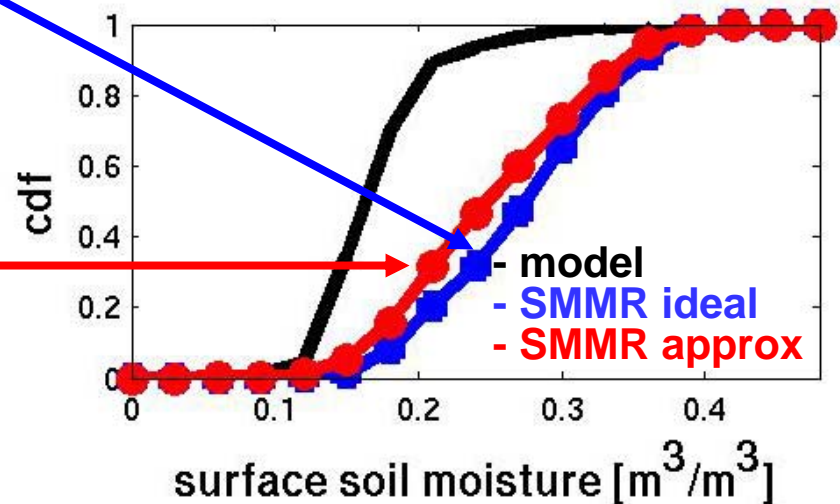
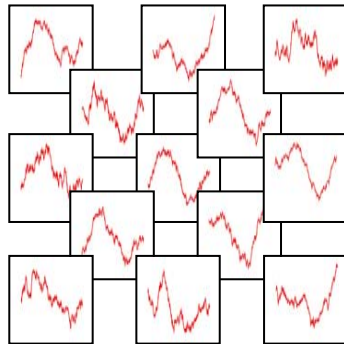
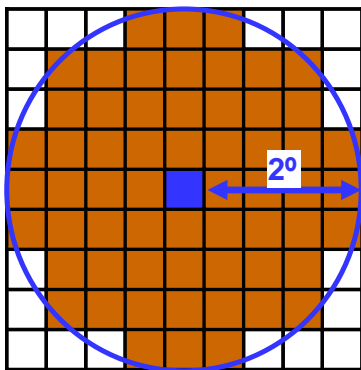
Ergodic substitution of variability in space for variability in time.

Soil moisture scaling for data assimilation



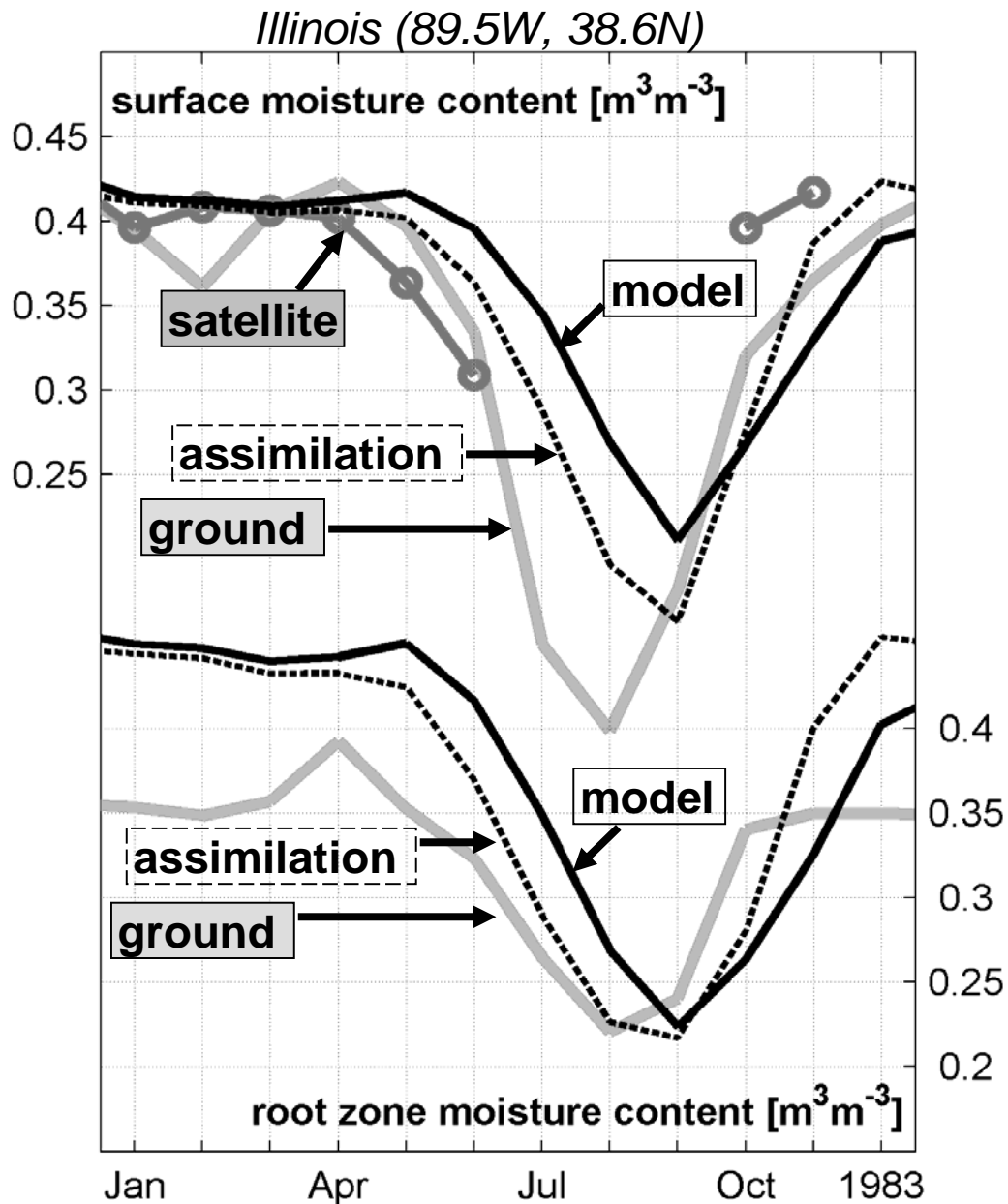
Ideally, compute local CDF from long time series at point of interest.

Approximate CDF from many 1-year time series at grid points within 2° from point of interest.



A single year of satellite data is sufficient for a good approximation of the ideal CDF.

Validation against in situ data



SMMR assimilation product has improved phase of annual cycle.